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Comparing Holt-Winters Variants Accuracy in Forecasting Indonesia LQ45 Stock Prices

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Abstract
This study applies the Holt–Winters method, an exponential smoothing approach incorporating level, trend, and seasonal components, to compare the predictive accuracy of four variants (multiplicative, additive, OR, and average) of Holt-Winters Method in forecasting stock prices of companies listed in the LQ45 index. The dataset consists of stock prices from 2016–2021 for training and January–February 2022 for testing, with forecasting accuracy evaluated using Mean Absolute Percentage Error (MAPE), visualized through boxplots, and assessed using the nonparametric Kruskal–Wallis test. The Holt–Winters computations were performed using Microsoft Excel, while boxplot visualization and the Kruskal–Wallis test were conducted using the R programming language. The results indicate significant differences in predictive performance among the four methods with p-value = 0.04059 in Kruskal-Wallis test. The Additive Holt–Winters method achieves the best performance with the lowest MAPE, while the multiplicative method performs the worst. Among LQ45 stocks, INDF records the lowest forecasting error (1.6799%), whereas TPIA exhibits the highest (83.0783%). These findings suggest that the additive Holt–Winters method achieves better forecasting accuracy for LQ45 stock prices under the observed conditions..

Keywords—Forecasting, Holt-Winter, LQ45, MAPE

1 Introduction

Forecasting is the process of predicting the value of a variable based on historical data and other relevant variables [1]. Among hundreds of companies listed on the Indonesia Stock Exchange, 45 stocks are selected based on high liquidity, large market capitalization, and strong fundamentals. This group, known as the LQ45 index, is considered representative for stock price forecasting analysis . One widely used method for time series forecasting, including stock prices, is the Holt–Winters method, which incorporates level, trend, and seasonal components.

Over time, several variants of the Holt–Winters method have been developed [2] [3]. In a previous study [4], ARIMA was compared with the Holt–Winters method and found that ARIMA achieved higher forecasting accuracy than Holt–Winters. This study aims to compare the accuracy of four Holt–Winters variants in forecasting LQ45 stock prices, namely the multiplicative, additive, OR, and average models. Forecast accuracy is evaluated using Mean Absolute Percentage Error (MAPE), which measures the percentage deviation between predicted and actual values. The comparison of the four methods is conducted using the nonparametric Kruskal–Wallis test. The results of this study are expected to provide alternative forecasting approaches for traders in making stock investment decisions.

A literature review by Hamidah et al. indicates that the accuracy of Holt–Winters models strongly depends on the data pattern [5]. The multiplicative model is more suitable for data with increasing trends and expanding seasonal fluctuations, whereas the additive model is more appropriate for data with relatively constant seasonal variations. This highlights the importance of identifying data characteristics prior to model selection.

The Holt–Winters method has been widely applied to time series data across various domains and countries, yielding diverse levels of accuracy. It has been used to forecast the Air Pollution Standard Index (APSI) in Surabaya

[6], food commodity prices in Pamekasan during 2012–2019 [7], and rainfall in Mataram during 2014–2018 [8]. In the tourism sector, the method has been applied to predict tourist arrivals in Indonesia [9], tourist visits in Sumenep Regency [10], and passenger numbers at Hasanuddin Airport during 2009–2019 [11]. During the COVID-19 pandemic, Holt–Winters was also utilized to forecast case numbers, where [12] reported that the additive model achieved good performance with MAPE below 10%, while [13] identified parameter combinations that produced relatively low forecasting errors. These findings demonstrate the flexibility of the Holt–Winters method in handling data with fluctuating patterns..

Efforts to improve the accuracy of Holt–Winters have also been conducted through parameter optimization. Study [14] shows that the Golden Section method can achieve high accuracy with MAPE below 10%, particularly for the additive model. Similarly, [15] applied this approach to obtain optimal parameters that minimize forecasting errors, although the results remain sensitive to the chosen threshold values.

Several studies have specifically compared different Holt–Winters variants. Study [16] found that the multiplicative model outperformed the additive model in forecasting monthly income data in Bangladesh. In contrast, [7] reported that the additive model yielded better performance. These differing results confirm that no single model is universally superior, as model performance depends on data characteristics such as stability and seasonal complexity [17]

In addition, some studies have compared Holt–Winters with other forecasting methods. Study [18] demonstrated that Holt–Winters provides more accurate results than Holt Double Exponential Smoothing in a sales forecasting case. This indicates that Holt–Winters, as an extension of exponential smoothing, has advantages in modeling data with both trend and seasonal components simultaneously.

2 Research Methods

2.1 Research Methodology

The research procedure in this study consists of the following systematic steps:

1. Collecting historical stock price data for all companies listed in the LQ45 index over a six-year period (2016–2021) from a securities provider, which are utilized as the training dataset for model development. The testing dataset consists of stock price data for a two-month period, namely January and February 2022.
2. Constructing the Holt–Winters Multiplicative model using optimal parameter values $(\alpha^*, \beta^*, \gamma^*)$that minimize the forecasting error, specifically MAPE-M.
3. Developing the Holt–Winters Additive model based on optimal parameters $(\alpha^*, \beta^*, \gamma^*)$that minimize MAPE-A.
4. Recording and storing the MAPE values (MAPE-M and MAPE-A) obtained from both models for further analysis.
5. Constructing the Holt–Winters OR model using the optimal parameter values $(\alpha^*, \beta^*, \gamma^*)$derived in the previous stage.
6. Developing the Holt–Winters Average model based on the optimal parameters obtained from the multiplicative and additive models in steps 2 and 3.
7. Performing forecasting using the Holt–Winters Multiplicative model and computing descriptive statistics of its accuracy, denoted as $MAPE_1$.
8. Performing forecasting using the Holt–Winters Additive model and computing descriptive statistics of its accuracy, denoted as $MAPE_2$.
9. Performing forecasting using the Holt–Winters OR model and computing descriptive statistics of its accuracy, denoted as $MAPE_3$.
10. Performing forecasting using the Holt–Winters Average model and computing descriptive statistics of its accuracy, denoted as $MAPE_4$.
11. Constructing boxplots to visually represent and compare the forecasting accuracy of the four methods based on their respective MAPE distributions.
12. Conducting a nonparametric statistical test to examine the equality of mean accuracy (MAPE values) among the four variations of Holt–Winters methods.

All computations in Steps 2–10 were performed using Microsoft Excel, while the graphical visualization in Step 11 and the Kruskal–Wallis test in the final step were conducted using standard packages in the R programming language [19] [20].

2.2 *Holt-Winters Method*

Time series forecasting refers to the application of analytical models to predict future values based on previously observed data [21]. In business contexts, time series data serve as a fundamental basis for current decision-making, as well as for projection and long-term planning activities [22].

The Holt–Winters method is an extension of the Exponential Smoothing (ES) approach. Exponential Smoothing generates forecasts by computing a weighted average of past observations, where the weights decay exponentially from the most recent observations to the oldest ones. The underlying assumption of ES is that more recent data points carry greater importance than earlier observations. However, the basic ES technique is not suitable for time series data that exhibit trend and/or seasonal patterns. To address this limitation, the Holt Exponential Smoothing (HES) method incorporates a trend component, although it remains inadequate for modeling seasonal variations. The Holt–Winters Exponential Smoothing (H-W ES) method further extends HES by integrating both trend and seasonal components, thereby enabling more accurate modeling of time series data characterized by these patterns [21] [23]. The Holt–Winters method is thus defined by three key parameters: level, trend, and seasonality.

In general, the Holt–Winters method is categorized into two primary variants. The multiplicative Holt–Winters model is suitable for time series data with seasonal variations that change proportionally with the level, resulting in increasing or decreasing fluctuations over time. In contrast, the additive Holt–Winters model is more appropriate for data with relatively constant seasonal variations, where the magnitude of seasonal effects remains stable across periods.

2.3 *Holt-Winters Method Variations*

Suppose: X_t = actual value at the end of time period t
α = smoothing constant for the level $(0 < \alpha < 1)$
β = smoothing constant for the trend $(0 < \beta < 1)$
γ = smoothing constant for the seasonal component $(0 < \gamma < 1)$
S_t = smoothed value at time period t
bt = smoothed trend value at time period t
It = smoothed seasonal index at time period t
L = length of the seasonal period
Ft+m = forecast for m periods ahead from time t

Holt-Winters Multiplicative

The Holt–Winters multiplicative method is defined by the following equations [12] [1]:

Overall level smoothing : $$S_t = \alpha \frac{X_t}{I_{t-L}} + (1-\alpha)(S_{t-1} + b_{t-1}) \quad (1)$$

Trend smoothing : $$b_t = \beta(S_t - S_{t-1}) + (1-\beta)b_{t-1} \quad (2)$$

Seasonal smoothing : $$I_t = \gamma \frac{X_t}{S_t} + (1-\gamma)I_{t-L+m} \quad (3)$$

Forecasting : $$F_{t+m}^{Multiplikatif} = (S_t + b_t m)I_{t-L+m} \quad (4)$$

The Holt–Winters multiplicative method determines the optimal parameter values (α,β,γ), denoted as $(\alpha^*,\beta^*,\gamma^*)$ which will minimize MAPE-M (α,β,γ) function which is defined as:

$$MAPE_{(\alpha,\beta,\gamma)}^{Multiplikatif} = \sum_{i=1}^{n} \left| \frac{A_i - F_{i,(\alpha,\beta,\gamma)}}{A_i} \right| \quad (5)$$

This optimal parameter values $(\alpha^*,\beta^*,\gamma^*)$ are subsequently used in the forecasting process.

Holt-Winters Additif

The Holt–Winters additive method is defined by the following equations [12] [1]:

Overall level smoothing: $$S_t = \alpha(X_t - I_{t-L}) + (1-\alpha)(S_{t-1} + b_{t-1}) \quad (6)$$

Trend smoothing: $$b_t = \beta(S_{t-1} - S_t) + (1-\beta)b_{t-1} \quad (7)$$

Seasonal smoothing: $$I_t = \gamma(X_t - S_t) + (1-\gamma)I_{t-L} \quad (8)$$

Forecasting: $$F_{t+m}^{Additif} = S_t + b_t m + I_{t-L+m} \quad (9)$$

In this study, the seasonal length is set to L=12. This study employs the **Holt-Winters method (L=12)**, favoring a monthly pattern to ensure a more robust seasonal structure. Unlike daily or weekly data—which are often skewed by market holidays—monthly data provides a clean, **12-month cycle** that allows mathematical models to clearly distinguish between permanent trends and annual fluctuations. Furthermore, monthly analysis captures recurring structural and psychological phenomena that are obscured in shorter timeframes, such as Window Dressing, the January Effect, and cyclical dividend distributions.

Therefore, 12 initial value for I are calculated as follows

$$I_1 = \frac{X_1}{Avg(X_1, X_2, X_3, \ldots, X_{12})}, \; I_2 = \frac{X_2}{Avg(X_1, X_2, X_3, \ldots, X_{12})}, \; I_3 = \frac{X_3}{Avg(X_1, X_2, X_3, \ldots, X_{12})}, \; \ldots, \; I_{12} = \frac{X_{12}}{Avg(X_1, X_2, X_3, \ldots, X_{12})} \tag{10}$$

The Holt–Winters Additive method determines the optimal parameter values (α,β,γ), denoted as (α*,β*,γ *) which will minimize MAPE-A(α,β,γ) function which is defined as:

$$MAPE_{(\alpha,\beta,\gamma)}^{Additif} = \sum_{i=1}^{n} \left| \frac{A_i - F_{i,(\alpha,\beta,\gamma)}}{A_i} \right| \tag{11}$$

This optimal parameter values (α*,β*,γ *) are subsequently used in the forecasting process.

Metode Holt-Winters OR dan Average

Based on the Holt–Winters Multiplicative and Additive methods, two additional variants can be derived, namely the Holt–Winters OR method and the Holt–Winters Average method.

The Holt–Winters OR method performs forecasting using both the multiplicative and additive models, and then selects the model that yields the lower MAPE error. The Holt–Winters OR method uses the formula 12

$$F_{t+m}^{OR} = \begin{cases} F_{t+m}^{Multiplikatif} & if \quad MAPE_{(\alpha,\beta,\gamma)}^{Multiplikatif} < MAPE_{(\alpha,\beta,\gamma)}^{Additif} \\ F_{t+m}^{Additif} & if \quad MAPE_{(\alpha,\beta,\gamma)}^{Multiplikatif} \geq MAPE_{(\alpha,\beta,\gamma)}^{Additif} \end{cases} \tag{12}$$

The Holt–Winters Average method generates forecasts by taking the average of the forecasts produced by the Holt–Winters Multiplicative and Additive methods, using formula 13::

$$F_{t+m}^{Average} = (F_{t+m}^{Multiplikatif} + F_{t+m}^{Additif})/2 \tag{13}$$

MAPE

The forecasting accuracy of the Holt–Winters method is evaluated using the Mean Absolute Percentage Error (MAPE), which represents the percentage error ratio. MAPE is calculated using Equation 14

$$MAPE = \sum_{i=1}^{n} \left| \frac{A_i - F_i}{A_i} \right| \tag{14}$$

Here, A_i denotes the actual value and F_i represents the forecasted value. In this study, n=39 corresponding to the number of observations over a two-month period (January to February 2022). MAPE is sometimes expressed as a percentage, which is obtained by multiplying the above equation by 100%.

3 Results and Discussion

The first step in the modeling process is to determine the parameter values (α,β,γ), denoted as (α*,β*,γ *) hat minimize the MAPE(α,β,γ) function. The optimal values (α*,β*,γ *) that yield the minimum MAPE_M are presented in Table 1. These optimal parameters (α*,β*,γ *) are then used to generate forecasts for the testing dataset (January to February 2022). The forecasted values are subsequently compared with the actual data, and the forecasting error is calculated using Equation 14. The results are reported in the MAPE_1 column of table 1.

Table 1: MAPE Values of LQ45 Stocks Forecasted Using the Holt–Winters Multiplicative Method

No.	Stock Code	MAPE_M Value (%)	Alpha*	Beta*	Gamma*	MAPE_1 (%)
1.	ADRO	21.3316	0.845154	0.567561	0.947116	70.1089
2.	AMRT	6.4701	0.996327	0.404219	0.963305	7.457
3.	ANTM	29.1831	0.945983	0.34049	0.983805	62.2315
4.	ASII	11.6846	0.828078	0.190731	1	18.1688

No.	Stock Code	MAPE_M Value (%)	Alpha*	Beta*	Gamma*	MAPE_1 (%)
5.	BBCA	6.0567	0.943174	0.21827	1	13.9268
6.	BBNI	8.167	0.939639	0.111494	1	13.2765
7.	BBRI	6.4316	1	0.139931	1	2.6526
8.	BBTN	14.6513	0.919976	0.225273	1	16.5632
9.	BFIN	10.4938	0.953797	0.203993	1	34.8461
10.	BMRI	8.722	0.932521	0.173723	1	15.2146
11.	BRPT	71.94782	0.285438	0.732296	0.918305	72.02829
12.	BUKA	-	-	-	-	-
13.	CPIN	10.0518	0.951087	0.036808	1	8.0856
14.	EMTK	14.6823	1	0.050088	1	19.3269
15.	ERAA	16.6873	0.826309	0.027428	1	12.7045
16.	EXCL	15.5864	1	0.417165	1	86.8939
17.	GGRM	8.5598	0.847692	0.122114	1	13.4332
18.	HMSP	6.4609	0.813985	0.105718	1	9.3560
19.	HRUM	28.7494	0.792108	0.319205	1	62.5383
20.	ICBP	6.5276	0.886665	0.938446	1	10.5395
21.	INCO	19.762	0.860073	0.461496	1	53.6881
22.	INDF	9.9904	0.848059	0.328466	1	22.4744
23.	INKP	13.3942	0.98537	0	1	4.6197
24.	INTP	11.0972	0.982915	0.203098	1	36.6563
25.	ITMG	23.0784	0.920641	0.421696	1	73.0655
26.	JPFA	21.897	0.935377	0.862827	1	57.2572
27.	KLBF	7.3743	0.81383	0.762785	1	4.6837
28.	MDKA	14.8499	1	1	0.6	10.6988
29.	MEDC	27.2279	0.888576	0.171828	1	48.0080
30.	MIKA	9.484	1	0.173511	1	12.8144
31.	MNCN	14.2246	0.990094	0.226936	1	4.9077
32.	PGAS	13.3096	0.918125	0.094697	1	5.0641
33.	PTBA	22.5956	0.920906	0.448911	1	67.3267
34.	PTPP	11.8762	1	0.064307	1	5.9479
35.	SMGR	9.4707	0.858018	0.230313	1	15.3583
36.	TBIG	9.5125	1	0.116904	0	26.5652
37.	TINS	27.3552	1	0.324257	0	62.3982
38.	TKIM	20.8142	1	0.307968	0	37.8857
39.	TLKM	7.4263	1	0.743141	0	7.6130
40.	TOWR	08.1399	0.84485	0.380556	1	21.6716
41.	TPIA	34.0231	0.999469	0.477791	1	92.1035
42.	UNTR	10.1043	0.873607	0.365131	1	34.7587
43.	UNVR	6.7357	0.823323	0.245346	1	7.1547
44.	WIKA	11.7142	0.935809	0.096566	1	12.4987
45.	WSKT	18.6199	0.922352	0.291782	1	18.6709
	Mean					**29.3919**
	Standard Deviation					**25.7571**
	Minimum					**2.6526**
	Maximum					**92.1035**
	Median					**17.366**

Table 1 shows that the average forecasting error for LQ45 stocks using the Holt–Winters Multiplicative method is 29.3919%, with a standard deviation of 25.7571%. The stock with the lowest forecasting error is BBRI at 2.6526%, while the highest error is observed for TPIA at 92.1035%. The stock with the code BUKA is excluded from the analysis due to insufficient data, as this company has only recently conducted its Initial Public Offering (IPO), resulting in an inadequate time series length for the application of the Holt–Winters method

The second step in the Holt–Winters Additive method is to determine the parameter values (α,β,γ), denoted as ($\alpha^*,\beta^*,\gamma^*$) that minimize the MAPE(α,β,γ) function. The optimal values ($\alpha^*,\beta^*,\gamma^*$) shown in Table 2. The optimal parameter values ($\alpha^*,\beta^*,\gamma^*$) produce the minimum MAPE_A. Parameters ($\alpha^*,\beta^*,\gamma^*$) are then used to generate forecasts for the subsequent two months. The forecasted values are compared with the testing dataset, which consists of data from January and February 2022, in order to obtain the forecasting accuracy measure denoted as MAPE_2 .

Table 2: MAPE Values of LQ45 Stocks Forecasted Using the Holt–Winters Additive Method

No.	Stock Code	MAPE_A Value (%)	Alpha*	Beta*	Gamma*	MAPE_2 (%)
1.	ADRO	51.681	0.998615	0.999243	0.929541	35.6037
2.	AMRT	7.8531	0.996327	0.404219	0.963305	5.7295
3.	ANTM	46.9717	1	1	0.98149	15.2867
4.	ASII	15.3808	1	0.128964	1	2.0360
5.	BBCA	9.297	1	0.057645	0	8.3975
6.	BBNI	10.9617	1	0.328514	0.716185	6.9861
7.	BBRI	7.5632	0.997659	0	0.877319	2.3236
8.	BBTN	17.169	1	0.284198	0.894098	8.7779
9.	BFIN	14.9985	1	0.137877	0.459011	30.2492
10.	BMRI	11.4792	1	0.065887	0.710885	8.9268
11.	BRPT	71.38493	1	0.89828	0.716172	57.0583
12.	BUKA	-	-	-	-	-
13.	CPIN	10.0872	1	0.026227	0.371127	12.6400
14.	EMTK	13.5216	1	0.050777	0.461344	14.6575
15.	ERAA	16.5999	0.894904	0.046784	1	21.4206
16.	EXCL	25.6842	1	0.080842	0	53.7546
17.	GGRM	9.0966	1	0.068038	0	2.6512
18.	HMSP	6.2709	1	0.068353	0	3.8978
19.	HRUM	52.8493	1	0.293407	0	49.7907
20.	ICBP	11.1212	1	0.872769	0	5.1669
21.	INCO	37.8952	1	0.115802	0	33.3855
22.	INDF	13.3114	1	0.43437	0	1.6799
23.	INKP	13.530	1	0.303016	0	3.8293
24.	INTP	10.7521	0.724879	0.180125	0.233924	21.1915
25.	ITMG	50.2274	1	0.209915	0.133982	46.5093
26.	JPFA	49.7734	1	0.172467	0.133982	30.1188
27.	KLBF	12.4731	1	0.029629	0.133982	2.6115
28.	MDKA	13.138	0.967642	0.0144	0.128319	4.8563
29.	MEDC	34.5106	1	0.140636	0.136109	10.7358
30.	MIKA	10.7369	1	0.117131	0.136109	4.9534
31.	MNCN	15.4398	0.983381	0.10632	0.131327	20.5286
32.	PGAS	32.6437	0.203258	1	0	12.4197
33.	PTBA	45.799	1	0.666032	0	36.4477
34.	PTPP	12.6474	1	0.069538	0	7.1132
35.	SMGR	8.6695	0.752819	0.266549	1	7.9208
36.	TBIG	9.4141	0.978392	0.091599	1	27.1617
37.	TINS	32.6472	1	0.222884	1	39.1288
38.	TKIM	24.9663	1	0	1	5.3835
39.	TLKM	12.1229	1	0.139124	1	2.1963
40.	TOWR	8.77	0.789782	0.726943	1	5.7866
41.	TPIA	11.4483	1	0.150693	0.3692	83.0783
42.	UNTR	15.5473	0.312481	0.223841	0.151409	14.2438
43.	UNVR	6.8925	1	0.115226	0.144564	5.9078
44.	WIKA	14.9889	1	1	0.144563	7.4562
45.	WSKT	24.8583	1	1	0.144564	14.0402
	Mean					**18.0463**
	Standard Deviation					**18.3504**
	Minimum					**1.6799**
	Maximum					**83.0783**
	Median					**9.8313**

Table 2 shows that the average forecasting error for LQ45 stocks using the Holt–Winters Additive method is 18.0463%, with a standard deviation of 18.3504%. The stock with the lowest forecasting error is INDF at 1.6799%, while the highest error is recorded for TPIA at 83.0783%

In the third step, the Holt–Winters OR method is applied as defined in Equation (9). The resulting MAPE values are presented in Table 3.

Table 3: MAPE Values of LQ45 Stocks Forecasted Using the Holt–Winters OR Method

No.	Stock Code	MAPE_M Value (%)	MAPE_A Value (%)	Selected H–W Method	MAPE_1 Value (%)	MAPE_2 Value (%)	MAPE_3 Value (%)
1	ADRO	21.3316	51.681	H-W*	70.1089	35.6037	70.1089
2	AMRT	6.4701	7.8531	H-W*	7.457	5.7295	7.457
3	ANTM	29.1831	46.9717	H-W*	62.2315	15.2867	62.2315
4	ASII	11.6846	15.3808	H-W*	18.1688	2.036	18.1688
5	BBCA	6.0567	9.297	H-W*	13.9268	8.3975	13.9268
6	BBNI	8.167	10.9617	H-W*	13.2765	6.9861	13.2765
7	BBRI	6.4316	7.5632	H-W*	2.6526	2.3236	2.6526
8	BBTN	14.6513	17.169	H-W*	16.5632	8.7779	16.5632
9	BFIN	10.4938	14.9985	H-W*	34.8461	30.2492	34.8461
10	BMRI	8.722	11.4792	H-W*	15.2146	8.9268	15.2146
11	BRPT	71.9478	71.3849	H-W+	72.0283	57.0583	57.0583
12	BUKA	-	-	-	-	-	-
13	CPIN	10.0518	10.0872	H-W*	8.0856	12.64	8.0856
14	EMTK	14.6823	13.5216	H-W+	19.3269	14.6575	14.6575
15	ERAA	16.6873	16.5999	H-W+	12.7045	21.4206	21.4206
16	EXCL	15.5864	25.6842	H-W*	86.8939	53.7546	86.8939
17	GGRM	8.5598	9.0966	H-W*	13.4332	2.6512	13.4332
18	HMSP	6.4609	6.2709	H-W+	9.356	3.8978	3.8978
19	HRUM	28.7494	52.8493	H-W*	62.5383	49.7907	62.5383
20	ICBP	6.5276	11.1212	H-W*	10.5395	5.1669	10.5395
21	INCO	19.762	37.8952	H-W*	53.6881	33.3855	53.6881
22	INDF	9.9904	13.3114	H-W*	22.4744	1.6799	22.4744
23	INKP	13.3942	13.53	H-W*	4.6197	3.8293	4.6197
24	INTP	11.0972	10.7521	H-W+	36.6563	21.1915	21.1915
25	ITMG	23.0784	50.2274	H-W*	73.0655	46.5093	73.0655
26	JPFA	21.897	49.7734	H-W*	57.2572	30.1188	57.2572
27	KLBF	7.3743	12.4731	H-W*	4.6837	2.6115	4.6837
28	MDKA	14.8499	13.138	H-W+	10.6988	4.8563	4.8563
29	MEDC	27.2279	34.5106	H-W*	48.008	10.7358	48.008
30	MIKA	9.484	10.7369	H-W*	12.8144	4.9534	12.8144
31	MNCN	14.2246	15.4398	H-W*	4.9077	20.5286	4.9077
32	PGAS	13.3096	32.6437	H-W*	5.0641	12.4197	5.0641
33	PTBA	22.5956	45.799	H-W*	67.3267	36.4477	67.3267
34	PTPP	11.8762	12.6474	H-W*	5.9479	7.1132	5.9479
35	SMGR	9.4707	8.6695	H-W+	15.3583	7.9208	7.9208
36	TBIG	9.5125	9.4141	H-W+	26.5652	27.1617	27.1617
37	TINS	27.3552	32.6472	H-W*	62.3982	39.1288	62.3982
38	TKIM	20.8142	24.9663	H-W*	37.8857	5.3835	37.8857
39	TLKM	7.4263	12.1229	H-W*	7.613	2.1963	7.613
40	TOWR	8.1399	8.77	H-W*	21.6716	5.7866	21.6716
41	TPIA	34.0231	11.4483	H-W*	92.1035	83.0783	92.1035
42	UNTR	10.1043	15.5473	H-W*	34.7587	14.2438	34.7587
43	UNVR	6.7357	6.8925	H-W*	7.1547	5.9078	7.1547
44	WIKA	11.7142	14.9889	H-W*	12.4987	7.4562	12.4987
45	WSKT	18.6199	24.8583	H-W*	18.6709	14.0402	18.6709

No.	Stock Code	MAPE_M Value (%)	MAPE_A Value (%)	Selected H–W Method	MAPE_1 Value (%)	MAPE_2 Value (%)	MAPE_3 Value (%)
	Mean						**28.37985**
	Standard Deviation						**25.56677**
	Minimum						**2.6526**
	Maximum						**92.1035**
	Median						**17.366**

Table 3 shows that the average forecasting error for LQ45 stocks using the Holt–Winters OR method is 28.37985%, with a standard deviation of 25.56677%. The stock with the lowest forecasting error is BBRI at 2.6526%, while the highest error is recorded for TPIA at 92.1035%. In Table 3, the “Selected H–W Method” column includes two symbols: H–W* denotes the Holt–Winters Multiplicative method, and H–W+ denotes the Holt–Winters Additive method.

In the fourth step, the Holt–Winters Average method is applied as defined in Equation (10). The resulting MAPE values are presented in Table 4.

Tabel 4 : MAPE Values of LQ45 Stocks Forecasted Using the Holt–Winters Average Method

No.	Stock Code	MAPE_4 Value (%)	No.	Stock Code	MAPE_4 Value (%)
1.	ADRO	52.8563	24.	INTP	28.8992
2.	AMRT	6.478	25.	ITMG	59.7458
3.	ANTM	38.7409	26.	JPFA	43.6407
4.	ASII	9.7852	27.	KLBF	3.1296
5.	BBCA	11.1741	28.	MDKA	4.3847
6.	BBNI	10.1778	29.	MEDC	28.9931
7.	BBRI	2.4229	30.	MIKA	5.2368
8.	BBTN	4.6212	31.	MNCN	7.8110
9.	BFIN	32.5090	32.	PGAS	6.3177
10.	BMRI	12.0505	33.	PTBA	51.7522
11.	BRPT	71.5221	34.	PTPP	6.3826
12.	BUKA	-	35.	SMGR	11.6264
13.	CPIN	7.0662	36.	TBIG	26.8133
14.	EMTK	16.9277	37.	TINS	50.7410
15.	ERAA	17.1279	38.	TKIM	19.8507
16.	EXCL	69.9252	39.	TLKM	4.8853
17.	GGRM	7.8571	40.	TOWR	21.6716
18.	HMSP	6.4374	41.	TPIA	87.5268
19.	HRUM	55.8476	42.	UNTR	24.4660
20.	ICBP	2.6967	43.	UNVR	2.1690
21.	INCO	43.2431	44.	WIKA	6.6985
22.	INDF	11.1809	45.	WSKT	15.0947
23.	INKP	4.1906			
	Mean				**23.0153432**
	Standard Deviation				**22.2769455**
	Minimum				**2.1690**
	Maximum				**87.5268**
	Median				**11.83845**

From Table 4, it can be observed that the average forecasting error for LQ45 stocks using the Holt–Winters Average method is 23.01534%, with a standard deviation of 22.276946%. The stock with the lowest forecasting error is UNVR at 2.1690%, while the highest error is recorded for TPIA at 87.5268%

A summary of the numerical descriptive statistics of MAPE for the four Holt–Winters methods is presented in Table 5.

Table 5: Summary of MAPE Statistics for the Four Holt–Winters Method Variants

Descriptive Statistics	MAPE			
	Holt-Winters Multiplicative Method	**Holt-Winters Additive Method**	**Holt-Winters OR Method**	**Holt-Winters Average Method**
Mean	29.3919	18.0463	28.37985	23.0153432

Standard Deviation	25.7571	18.3504	25.56677	22.2769455
Minimum	2.6526	1.6799	2.6526	2.1690
Maximum	92.1035	83.0783	92.1035	87.5268
Median	17.3660	9.8313	17.3660	11.83845

From Table 5, it can be observed that the Holt–Winters Additive method provides the best forecasting performance for LQ45 stocks, as it yields the lowest descriptive statistical measures (mean, standard deviation, minimum, maximum, and median) compared to the other three forecasting methods.

The results in Tables 1–4 indicate that INDF, when forecasted using the Holt–Winters Additive method, has the lowest forecasting error at 1.6799%. In contrast, TPIA exhibits the highest forecasting error under both the Holt–Winters Additive and Multiplicative methods.

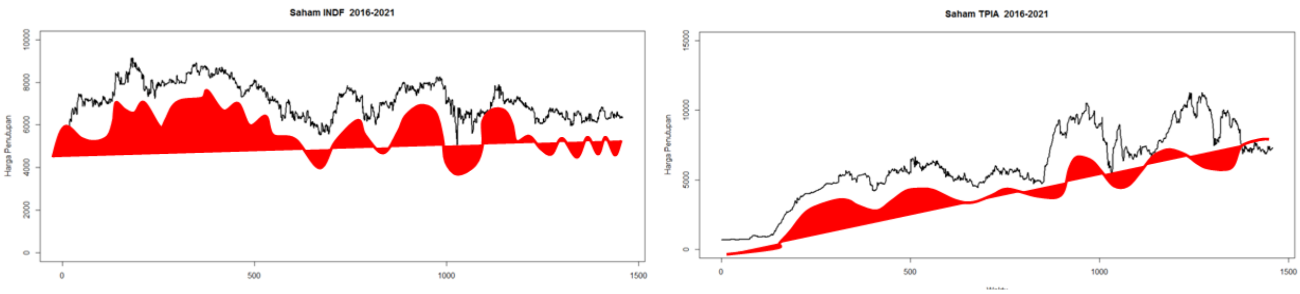

Figure 1: Stock Price Patterns of INDF (left) and TPIA (right) from 2016–2021

From Figure 1, it can be observed that INDF exhibits a seasonal fluctuation pattern that is closer to a monthly cycle, whereas TPIA shows a longer seasonal fluctuation pattern than monthly. In terms of trend, INDF tends to fluctuate around a relatively stable level, while TPIA demonstrates an upward trend with noticeable fluctuations.

To visualize the distribution of MAPE values for each forecasting method, a boxplot diagram can be used, as shown in Figure 2.

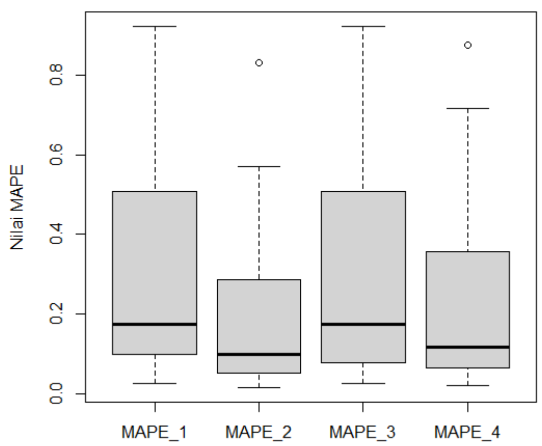

Figure 2: Boxplot Diagram of MAPE for the Four Holt–Winters Method Variants

From Figure 2, it can be observed that the Holt–Winters Additive and Holt–Winters Average methods produce outliers in their MAPE distributions. Each method contains one outlier, and both are upper outliers. In terms of distribution, the MAPE values tend to be right-skewed. Based on the measures of central tendency, the Holt–Winters Additive method exhibits the lowest median value, approximately 0.098313 or 9.8313%.

To determine whether the mean MAPE values of the four methods are statistically equivalent or significantly different, the nonparametric Kruskal–Wallis test is applied. The results obtained using R are as follows: Kruskal-Wallis chi-squared = 8.2789, df = 3, p-value = 0.04059. At a significance level of $\alpha = 0.05$, it can be concluded that there is a statistically significant difference in forecasting accuracy, as measured by MAPE, among the four methods in forecasting LQ45 stock prices. The Holt–Winters Additive method demonstrates the best performance, while the Holt–Winters Multiplicative method yields the lowest accuracy based on MAPE. The choice between these methods depends on how seasonal "swings" relate to price levels. The Multiplicative model assumes fluctuations grow proportionally with the trend, whereas the Additive model assumes they remain constant in absolute terms. For LQ45 blue-chip stocks, the Additive method is often more accurate because these mature companies exhibit stable, linear growth rather than exponential surges. LQ45 stocks are "mature & predictable," while Holt-Winters Additive is "linear & stable." The combination of the two produces an efficient forecasting model because the model isn't forced to assume that price fluctuations must increase proportionally with stock price increases, but rather consistently follow the established annual business cycle.

4 Conclusion

- Among the four Holt–Winters variants, the Holt–Winters Additive method demonstrates the best performance in forecasting LQ45 stock prices, as it yields the lowest descriptive statistical measures (mean, standard deviation, minimum, maximum, and median) compared to the other three methods.
- Based on the boxplot analysis, both the Holt–Winters Additive and Holt–Winters Average methods exhibit one upper outlier each in their MAPE distributions. These outliers are associated with the forecasting results for stock TPIA.
- The Kruskal–Wallis chi-squared test at a significance level of $\alpha = 0.05$ indicates a statistically significant difference in MAPE values among the four Holt–Winters variants in forecasting LQ45 stocks. The Holt–Winters Additive method provides the highest accuracy, while the Holt–Winters Multiplicative method shows the lowest performance based on MAPE.
- The lowest forecasting errors for the Holt–Winters Multiplicative and Holt–Winters OR methods are observed for stock BBRI, with MAPE values of 2.6526% for both methods. For the Holt–Winters Additive method, the lowest error is obtained for stock INDF with a MAPE of 1.6799%, while for the Holt–Winters Average method, the lowest error is observed for stock UNVR with a MAPE of 2.1690%.

5 Suggestion

This study can be further extended by comparing similar cases analyzed using alternative approaches, such as Backpropagation and other Machine Learning models.

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